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Anticipation of Mid-Span Deflection at Ultimate Load for Concrete Beams Strengthened by FRP Bars Using Artificial Neural Networks

Abdulnasser Mohammed Abbas
Department of Civil Engineering ,University of Basrah
nasser21272@gmail.com

Abstract

A mid-span deflection of concrete beam strengthened by FRP bars has been anticipated. A case of simply supported beam loaded by two point loads has been simulated by using artificial neural networks (ANNs) which are involved in MATLAB package, version 9.0.0.341360 (R2016a). The proposed model presupposes 60 beam specimens to collect the required data for the neural pattern. A set of 8 input variables was selected to construct the proposed neural pattern; these are, beam dimensions, concrete specifications, and FRP properties. While the mid-span deflection at the ultimate load, will be the output inconstant. The use of 9 nodes in the hidden layer is active in predicting the mid-span deflection. A comparison between the gained results and the past experimental data shows that the proposed neural pattern gives a reasonable anticipation with an overall error of 8.2 %.

Key words: Mid-span deflection, Flexural behavior, FRP bars, Artificial neural networks.

الخلاصة

تم تخمين الهطول عند الحمل الاقصى لمنتصف عتبة خرسانية مسلحة بقضبان تسليح بوليمرية. تمت دراسة حالة عتبة بسيطة الاسناد معرضة الى حملين متناظرين باستخدام الشبكات العصبية الاصطناعية الموجودة ضمن برنامج الماتلاب ذي الاصدار (R2016a) 9.0.0.341360. لقد تم استخدام 60 عينة لغرض جمع البيانات المطلوبة لمحاكاة النموذج. كما تم اختيار مجموعة المدخلات من 8 متغيرات. تمثلت بأبعاد العتب، خصائص الخرسانة، وخصائص قضبان التسليح البولمرية. في حين كانت بيانات الإخراج هي الهطول في منتصف العتب عند الحمل الاقصى. لقد وجد ان استخدام 9 عقد في الطبقة المخفية فعالا لتوقع الهطول في منتصف العتبة. لقد بينت المقارنة بين النتائج المكتسبة مع البيانات التجريبية السابقة أن النموذج المقترح أعطى تقييما معقولا ومعدل خطأ عام يساوي 8.2٪.

الكلمات المفتاحية : انحراف منتصف الفاصل، السلوك المرن، أشرطة FRP، الشبكات العصبية الصناعية.

1. Introduction:

When a structural concrete member, which is reinforced using conventional steel rebars, becomes under offensive environments, like de-icing chlorides or marine surroundings, the concrete may exposed to sever damages due to corrosion and oxidized. Therefore, other materials that show high strength against corrosion have been progressively used, such as Fibre Reinforcement Polymers (FRP). These materials are applied nowadays in different kinds of civil engineering constructions such as marines structures, foundations base of electrical and reactor tools, and floor concrete sheets in aggressive chemical milieu (Maher *et.al.*, 2015). FRP are structural reinforcing bars made of fibers held in a resin polymeric binder. FRP are manufactured in several types of fibers like Carbon (CFRP) and Glass (GFRP). Besides resistance of corrosion, FRP bars have many other characteristics as compared with steel rebars, some of these are high tensile strength, lightweight, linear elastic to failure, and lower strain at failure (ACI 440.1R-06, 2006).

Studies of fiber-reinforced polymer (FRP) bars have been made theoretically and experimentally to investigate the flexural behavior of concrete members reinforced by (FRP) bars (Almusallam, 1995; Ashour *et.al.*, 2006; Chaallal *et.al.*, 1995; Ehab *et.al.*, 2002; Pecce *et.al.*, 2000). Some of these investigations stated that the deflection of concrete beams reinforced by FRP is bigger than similar samples of RC beams reinforced by steel; the diagram of their load-deflection is in a straight line (Saadatmanesh *et.al.*, 1991; Victor *et.al.*, 2002). However, there are still less researches to anticipate the deflection of concrete members reinforced with FRP elements. This study aims to investigate a mid-span deflection at ultimate load for simply supported concrete beams reinforced by FRP using artificial neural networks.

2. Artificial Neural Networks:

Artificial Neural Network is a mathematical model which uses available empirical datum to predict the behavior of any structure under different testing conditions. Actually, the smallest mathematical function of any artificial neural network is called artificial neuron. This function consists of three basic principles: multiplication, collection and stimulation (Kenji , 2011), see figure (1).

It is utterly true that the working basics and rule sets of artificial neuron seems to be blank; however the total potential and computation power of these structures come to life when they are internally joined into artificial neural networks, see figure (2). Therefore, basic and plain rules of these ANNs may lead to a sort of complications.

To use the artificial neural network system, the ANN should be learned to deal with the form of the given dilemma. The ANNs can act as the same of biological neural networks whose can study their responses of the rule of incomes that they earn from their habitat.

The datum comes into the structure of an artificial neuron by means of inputs that are weighted, in which every input can be independently times by a weight, and then, the structure of an artificial neuron accumulates the weighted inputs. Finally, an artificial neuron goes along the treated information as an output data (Kenji,2011).The mathematical statement of an artificial neuron pattern can be simplified in equation (1).

$$y(k) = F\left(\sum_{i=0}^{m} w_i(k).x_i(k) + b\right) \quad (1)$$

Where:

x_i (k): input value at time (k).

w_i (k): weight value at time (k).

b: bias

F: transfer function

y_i (k): output value at time (k).

m: number of input variables

From the equation mentioned above, it can be notice that the considerable anonymous variable is the transfer function, which describes the features of artificial neuron, and it could be any mathematical model. Generally there are two possible output magnitudes, zero and one. It will be one when the input value fits the specific neuron, as versus as, the value will be zero.

3. Research Methodology:

3.1. Structure of Suggested Neural Model and Data Election:

To predict a mid-span deflection at the ultimate load for a concrete beam, reinforced by FRP bars, an artificial neural simulation is made depending on MATLAB version 9.0.0.341360 (R2016a). In this study, the case of simply supported beam loaded by two point loads is considered, see figure (3***)***.

In the beginning, a relation between input and output variables should be simulated. To do this; the algorithm of feed-forward back-propagation will be used. In order to construct and learn the neural networks, the process of trial and error is used for learning types, hidden layers, and training parameters.

The selection of data for the suggested neural model depends on the available past researches (Begg *et.al.*, 2006; Imam *et.al.*, 2014; Kamanli *et.al.*, 2012; Raheman *et.al.*, 2013; Yost *et.al.*, 2001; Ashour, 2004; Tomlinson *et.al.*,2014; Kassem *et.al.*, 2011; Zhang L., *et. al.*, 2014; Aiello M. *et. al.*, 2000; Kishi N., *et. al.*, 2005; Al-Sunna R., *et. al.*, 2006; Rasheed *et.al.*, 2004; Abdul Hamid *et.al.*, 2013), in which overall number of (60) beam specimens were gathered to construct a data base. Various input parameters to the whole data set should be considered for the training group. However, the training process capacity built by alternative election from the data set, or else, they may be taken randomly by the computer system.

To gain reasonably accurate results, the available data for the neural pattern should be divided into two categories, training and testing sets. In the recent work, forty eight (48) specimens were used for the training group and twelve (12) samples were used for the testing set.

3.2. Description of Variables:

It is crucial to select the input parameters to gain a powerful network. However, the output parameters depend on the type of the network.

In the present work, a mid-span deflection at ultimate load (*d*) is considered as an output variable. While the input parameters will be eight, these are:

a- Beam dimensions, width (b), depth (h), span length (L), and shear span (m=a/L), where (a) is the shear span (mm).
b- Cylinder compressive strength of concrete (f'_c).

c- Cross sectional area (A_f), modulus of elasticity (E_f) and tensile strength (f_u) of FRP bars.

The input variables will be represented in the input layer by eight nodes, while there will be only one node for the output layer. The domain of input and output parameters are listed in table (1) and table (2).

3.3 Hidden Layers and Their Nodes:

The network implementation decides the hidden layers and their inside nodes, there is no principles available to determine their accurate number. Sometimes it begins by a tiny number and gradually increased by trial and error until the required simulation of the networks is attained. Actually, the activity of network will be heavy and slow if there are a large number of nodes, and this may give rise to complicate preference of the testing set. While it may be fail to pick up, if this number is very poor. However, and to get a gorgeous achievement of training and testing sets, network with a minimum error and convenient number of hidden layer nodes will be chosen by the process of trial and error.

To designate appropriate network, back propagation (Levenberg-Marquardt) neural network with various orders was considered. In meantime, several networks with different activation functions, tansig (Hyperbolic tangent), logsig (Logistic sigmoidal), and purelin (Linear) were tested and the optimal topology was gained by taking network with training of minimum inaccuracy. The obtained data demonstrates that the one hidden layer with nine nodes pattern bear reasonable performance with less error for the output variables. The structure of this network consists of tansig function with (9) nodes for the hidden layer, while a purelin function was used for the output layer, figure (4). This structure results in a better performance with MSE of (0.0026) for the testing set, (0.0014942) for the training group, and the number of epochs is (55), as shown in figure (5). The properties of the used neural pattern are shown in table (3).

4. Evaluation of Networks Performance:

In this study, artificial neural network was used to expect the mid-span deflection at ultimate load for concrete beams reinforced by FRP bars. To evaluate the performance of the selected neural network, a comparison between the present work (d_{ANN}) and the past experimental studies have been done, see table (4). It can be seen from these results that the proposed model gives quite accurate results. The ratio between the deflection values obtained from the used neural model to the available experimental data varies from (0.817) to (1.235) with an average of (1.039).

On the other hand, a statistical calculation was done to compare between the actual values of deflection and the predicted ones. The four statistical indexes are:

a- MAE: Mean Absolute Error,
b- MAPE: Mean Absolute Percentage Error
c- RMSE: Root Mean Squared Error, and
d- FOV: Fraction of Variance

These indexes are presented in equations (2) to (5), respectively.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|u - v\right| \tag{2}$$

$$\text{MAPE} = \left[\frac{1}{n}\sum_{i=1}^{n}\left|(u-v)/u\right|\right]\times 100 \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(u-v)^2} \tag{4}$$

$$\text{FOV} = 1 - \sum_{i=1}^{n}(u - v)^2 / \sum_{i=1}^{n}(u - \overline{u}) \tag{5}$$

Where:

u is the actual value,

v is the predicted value,

$\overline{u}$ is the mean of the actual values, and

n is number of specimens.

The obtained results are presented in table (5). It can be seen that for the predicted deflection of the neural model, the values of MAE, MAPE, RMSE, and FOV are (0.724, 2.47, 1.729, and 0.95) respectively. The gained values indicate that the network model agreed with the experimental values, therefore the neural network model can anticipate deflections elegantly with an average error of 8.2%.

5. Results and Discussion:

To evaluate the accuracy of the used neural model, a regression test was made for the predicated values of mid-span deflection with the actual results. The index of this test is called coefficient of correlation (R), when R becomes as close as possible to (one), the correlation is then so perfect. Figure (6) illustrates the correlation test for the used neural model with the experimental values for the training group with correlation value of (R =0.99277). However, figure (7), indicates the same relation, but for the testing group with value of correlation equals to (R= 0.98633). Therefore, and because the obtained values of the index R reached to (one), with an error of 0.72 % and 1.36 % for the training and testing groups respectively, it can be stated that the proposed neural model accurately simulates the experimental results.

6. Conclusions:

Mid-span deflection at ultimate load for simply supported concrete beam reinforced by PRF bars was investigated by using artificial neural networks. The main remarkable conclusions are:

1. The obtained values of mid-span deflection are compared with the existed experimental information and the ratio between them is found to be varied from (0.817) to (1.235) with an average of (1.039).
2. The gross average error of the neural model for the anticipation of mid-span deflection leads to (8.2 %). This means that the used neural pattern gives gorgeous results.
3. The correlation index R reaches to one, with an error of (0.72 %) for the training group and (1.36 %) for the testing group, which indicates that the correlation is spectacular.
4. The performance of the artificial neural network to predicate the mid-span deflection at ultimate load has been confirmed efficiently.

7. Acknowledgement:

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Table (1) Input parameters

Item	**Parameters**	**Amplitude**	
		Min.	**Max.**
Beam	Width *b* (mm)	80	500
	Depth *h* (mm)	100	550
	Length *L* (mm)	400	3400
	Shear span ratio *m (a/L)*	0.313	0.470
	Cylinder compressive strength of concrete f'_c (MPa)	22.9	85.6
FRP	Area A_f (mm^2)	50	1134
	Tensile strength f_u (MPa)	347.5	1988
	Modulus of elasticity E_f (MPa)	32670	122000

Table (2) Output parameters

Parameter	**Amplitude**	
	Min.	**Max.**
Mid-span deflection *d* (mm)	8.1	131.4

Table (3) Features of used neural pattern

Network	***Number of nodes***		***Number of Iterations***	***MSE***	
	Hidden layer	***Output layer***		***Training set***	***Testing set***
9 – 1	9	1	55	0.0014942	0.0026

Table (4) Actual and predicted mid-span deflection at ultimate load

Beam Item	***Mid-span deflection (mm)***		d_{ANN}/d_{EXP}
	Actual d_{EXP}	***predicted*** d_{ANN}	
1	32.86	30.30	0.922
2	36.43	36.96	1.015
3	45.00	50.50	1.122
4	40.30	40.50	1.005
5	42.30	45.40	1.073
6	42.00	48.50	1.155
7	48.80	52.67	1.079
8	53.87	53.87	1.000
9	45.00	46.59	1.035
10	8.10	10.00	1.235
11	13.83	13.94	1.008
12	16.87	13.78	0.817

Table (5) Statistical indexes

Index	MAE	RMSE	MAPE	FOV
Used neural pattern	0.724	1.729	2.470	0.950

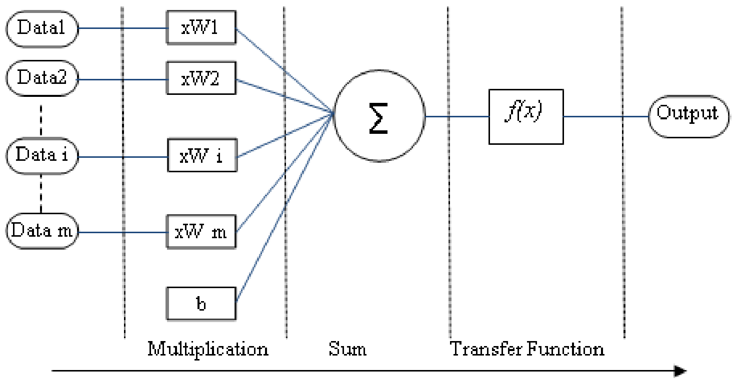

Figure (1) Working presinciple of an artificial neuron (Kenji , 2011)

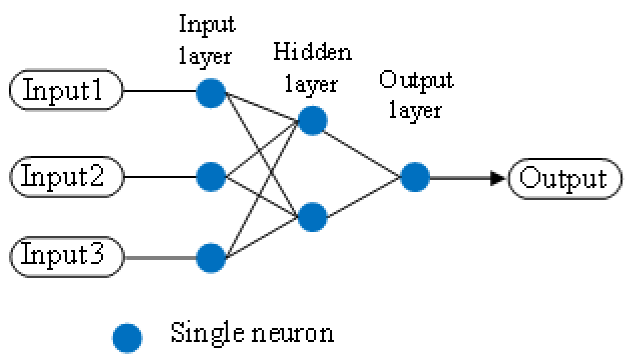

Figure (2) Simple artificial neural network (Kenji , 2011)

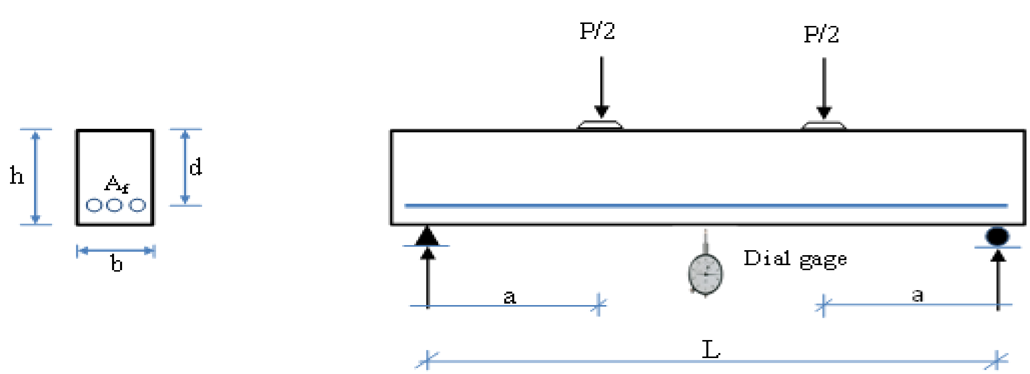

Figure (3) Concrete beam loaded by two point loads

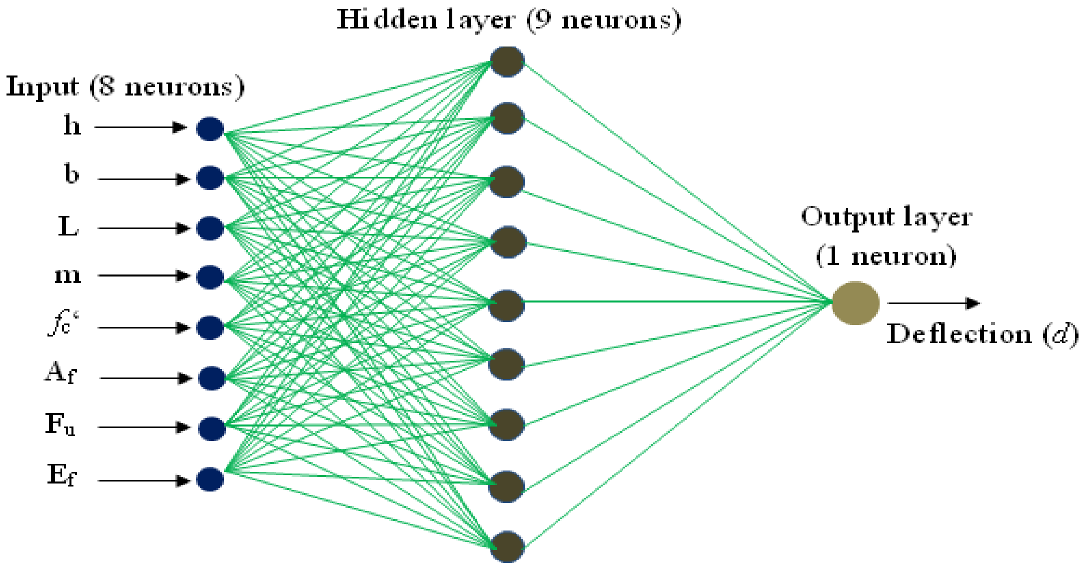

Figure (4) Topology of used neural pattern

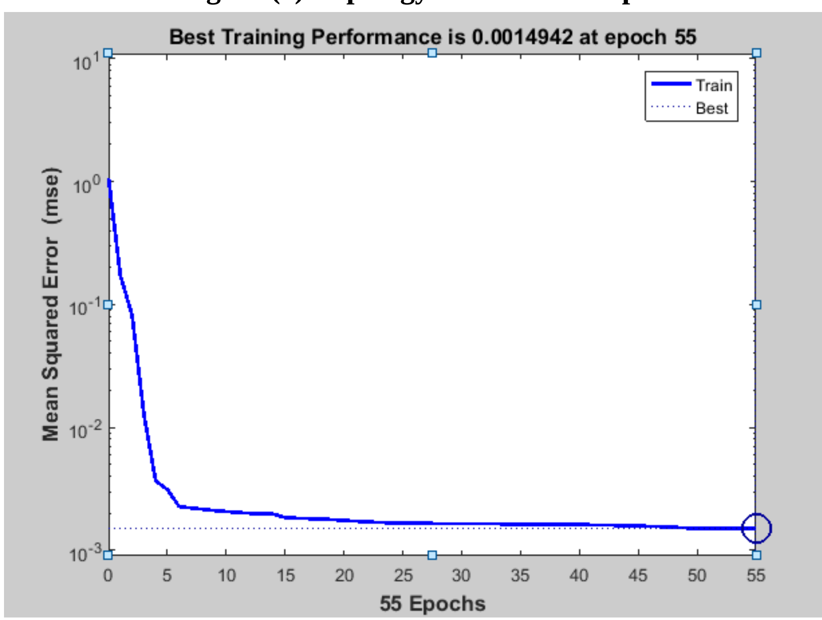

Figure (5) Number of epochs for training group

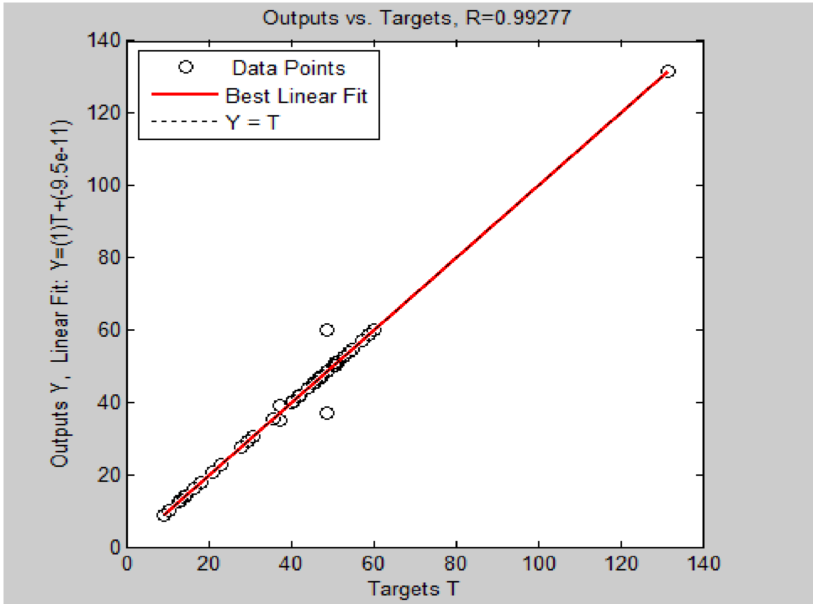

Figure (6) Regression analysis (training set)

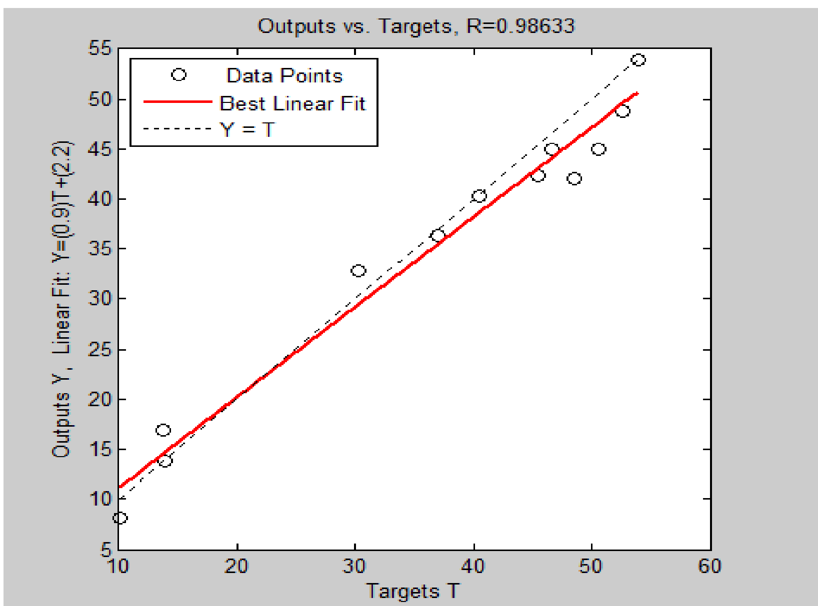

Figure (7) Regression analysis (testing set)